Use of Machine Learning Techniques to Create a Credit Score Model for Prepaid Basic Services in East Africa. Case Study: Airtime Loans

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Abstract

Basic services such as electricity, water, sanitation, health and education are required to enable economic development. Access to mobile services has grown faster than access to these basic services and has many benefits including communication, internet, information and mobile banking. Due to affordability constraints in many developing countries, many of these services are being offered as prepaid services as opposed to paying at the end of the month. As a response to cashflow issues and unreliable access to money, credit provision for these services is becoming increasingly common. Credit scoring models are used in the financial services industry to determine whether or not a customer is likely to repay a specific loan. Airtime lending is a relatively new service and at present, such credit models are not used. Most companies use business rules to reduce default rates and remain profitable. The airtime lending default rate is typically lower than that in banks and microfinance institutions (MFIs) but is likely to grow as the service is offered more widely. In this paper, the models proposed for MFIs are reviewed and that knowledge is built upon to create a model for airtime lending. Over three million loans belonging to more than 41 thousand customers with a repayment period of three months were analysed. Logistic regression, decision trees and Random Forest were evaluated for their ability to classify default using a number of cross-validation approaches and the latter model performed best. The empirical analysis offers a number of insights. When the default rate is below 2%, it is better to offer everyone a loan. For higher default rates, the model will substantially enhance profitability. The model quadruples the tolerable level of default rate for breaking even from 8% to 32%. Nonlinear classification models offer considerable potential for credit scoring, coping with higher levels of default and therefore allowing for larger volumes of customers.

1 Introduction

In East Africa, electricity is bought in terms of tokens. One buys a token worth a specific amount and they are given a token number. They load a token to there meter and they get electricity. When the units of the token are over, electricity is cut. The same applies to water, some solar lamps and now

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there are also introducing the same concept to cooking gas. The idea behind this is, the providers realized that consumers are willing to pay for services but based on the cash that they have. An example is that consumers were not willing to buy oil of 5 litres but if the same oil was repackaged to portions of specific amount like \$0.5, they bought it. In this model, consumers need to have money with them at all times just in case they use up all the available tokens units for that service. Due to the importance of the services, the consumers welcomed the idea of credit.

Airtime is the amount of money paid to mobile telecoms by a telecom subscriber in order to access mobile services such as making calls, sending SMS or broadband [2]. This is done by purchasing scratch cards of particular denominations and entering the relevant codes. This credits the customer's balance. Another method of purchasing airtime is by using mobile money. Airtime amounts are available from as little as \$0.5.

Airtime in Africa is quickly becoming a basic commodity among the rapidly growing middle class [1]. One's failure to acquire airtime to communicate or load data bundles can prove a deterrent for the middle-income earner [3]. Many mobile network operators (MNOs) active in emerging markets have spotted this as an opportunity to offer their subscribers short-term airtime loans at a moderate interest rate of around 10% [4]. This new service has the potential to increase their average revenue per user. Repayment of the loan is achieved once the subscriber's account is credited. However, the risks of defaulting need to be analyzed to obtain a deeper understanding of this new product. In this paper we will define defaulting as a subscriber failing to pay the loan within a specified time frame. This risk transcends most institutions that lend money to their customers. To mitigate this risk, credit scoring models are required to assess the capability of the customer to pay a certain amount within the specified period.

Credit scoring is a tool used in the decision making process of whether to accept or reject a loan [5]. The advantages of using this include: enabling faster credit decisions; reducing the cost of credit analysis; and monitoring the portfolio of existing accounts [6]. Credit scoring models are typically built using a variety of historical financial data obtained from the customers. However, in developing countries where there is a large population of unbanked adults, such data is not readily available [7]. Therefore, there is a need to search for alternative data in order to determine whether a customer is creditworthy. MNOs can monitor the customer's calls and recharge history to determine their creditworthiness because they have access to such data.

We have identified two distinct mechanisms in the prepaid basic services . In the first, the service provider offer service loans to customers and bear the risk of non-performing loans. An example of a company that uses such a mechanism is Safaricom. The service is called 'okoa jahazi'. When a subscriber runs out of airtime, they are able to borrow money amounting to the amount topped up in the last seven days. They also have to repay the money within five days [10].

The second mechanism involves a partnership between the service provider and a third party lender such that the provider provides access to the customers and service. Then the risk is transferred to the third party. An example of a lender which relies on such a partnership is ComzAfrica. Within such an ecosystem, service providers tend to be protective of their customers' privacy which limits the amount of data shared with the lenders. Consequently, lenders have little information about their customers. This is the mechanism that we will study in this paper.

The paper is organized as follows. Section 2 contains the background of the lending industry and the case study, ComzAfrica. Section 3 provides the methodology, Section 4 gives the results of the research and Section 5 concludes and discusses future work.

2 Background

2.1 Financial Lending Industry

The main actors in this industry are financial institutions and money lenders who lend money to whoever they deem creditworthy. These loans are usually monetary and have to repay within a specific time frame with interest. This industry has evolved over time and extends beyond financial institutions to include players in other industries such as the telecommunication sector [1].

In most emerging economies, a significant number of MNOs have joined this industry [1] and offer credit services in the form of mobile money and airtime [2]. Subscribers can apply for airtime loans and it is at the discretion of the MNO to offer the airtime loan at a specified interest rate to be repaid within a particular time period [4]. While mobile lending is innovative and has potential to improve financial inclusion, it also poses challenges for regulators.

2.2 Credit Scoring in Related Industries

The concept of credit scores dates back to the 1950s [9], when the lending decisions were made by loan officers. This method was not effective as it relied on the subjective judgment of the loan officer. Furthermore, there was no accurate way of determining and monitoring the defaulters and non-defaulters.

In the 1950s, Bill Fair and Earl Isaac introduced a statistical number designed to represent the creditworthiness of an individual and most of the time their predictions were accurate. It was not until the 1970s that these credit scores became an important component of the lending industry. Lenders from banks to microfinance institutions currently use credit scoring to measure a potential borrower's creditworthiness [8].

Airtime lending is unique because loan repayment is encouraged by the customer's need to use services such as calling, messaging, access to Internet and USSD applications. A customer cannot use these services if they have no airtime. Buying and loading the airtime onto the customer's account provides a direct loan repayment process. This incentive structure cannot be seen in the other industries.

2.3 ComzAfrica

ComzAfrica is a micro-lending company operating in 16 countries across Africa and Asia. ComzAfrica has built an Airtime Credit Service (ACS) which allows users to access airtime on credit basis. Given that the users do not always have access to a retailer or direct funds, this service allows them to access airtime on a credit basis and make calls or send messages [7].

The service is offered through two main interfaces; Short Message Service (SMS) and Unstructured Supplementary Service Data (USSD). When a customer makes an airtime on credit request using one of the interfaces mentioned above, the system will check if they meet eligibility criteria. If so, the airtime requested is loaded onto their account. Repayment happens when the customer performs their next recharge [7].

3 METHODOLOGY

3.1 Literature Meta-Analysis

The main purpose of this part of the study is to understand the application of credit scoring in the financial services industry. Based on previously published research, it is possible to learn what data has been used, features extracted and models constructed. This provides a basis for developing a credit scoring system for the mobile airtime lending industry. The literature review did not offer any papers specifically addressing the airtime lending industry. Instead papers were identified that undertook research in related fields and offer some insights. The following paragraphs explain our criteria for selecting papers and our results are summarized in Section V of this paper.

While the focus is on credit scoring in the mobile money industry, there were few papers in this area. However there is much to learn from published studies about the microfinance industry in developing countries. The best performing models were selected and described in Table 1. Evaluation criteria presented in the papers included area under the receiver operating curve (AUC) [12] [13] [15], Kolmogorov-Smirnov Statistic (KS) [15] and expected misclassification cost (EMC) [13] [12].

The meta analysis selection criteria endeavored to find statistically robust studies whereby the number of customers and loans were large enough to obtain statistically significant results. The criteria also involved selecting papers that performed credit scoring research in developing countries. The objective was to find research linked to countries facing similar challenges in terms of data availability on prospective applicants and countries with a similar economic and development setting, where the case study company operates.

Table 1: Summary of best performing models

Papers	#Variables	Model	Defaulters	Non-Defaulters	ACC %	N
María-Dolores et al [13]	39	MLP (BFGS Quasi-Newton training)	2673	2778	88.33	5451
Joris Van Gool et al [15]	16	Binary Logit Model + WOE Coding	1661	5061	76.8	6722
Blanco et al [12]	39	MLP	2673	2778	93.22	5451
Ibtissem B. [14]	10	Logistic Regression	1994	3028	–	5022

Table 2: Variables highlighted by the meta analysis

	Papers			
Variables	[13]	[15]	[14]	[12]
Previous Loan Grant	Y	–	–	Y
Loan Grant	Y	Y	Y	Y
Loan Denied	Y	–	–	Y
Gender	Y	–	Y	Y
Gender	Y	–	Y	Y
Age	Y	Y	Y	Y
Interest Rate	Y	–	–	Y
Cycles	–	Y	–	–
Beginning Month	–	Y	–	–
number of previous loans	–	–	Y	Y
previous loan default	–	–	Y	–
Marital Status	Y	Y	–	Y

The paper selection criteria also required the variables used to be similar to the variables available for the case study. The similarity test involved checking how the variables described a prospective loan applicant and its relevance to the model measured via statistical significance. Finally these variables that were significant, employed in the models developed in the papers, and related to the mobile industry were listed in Table 2.

Some variables used in different industries such as MFIs and banks are not available in the airtime lending industry. These variables mostly relate to the financial environment of the home or business associated with the prospective loan applicant. These variables include: net earnings of business, business capital, net earnings of household, and household capital.

The next step was to investigate the many classification models used in each study and determine the reasoning behind the choice of models and selected techniques. The model with the best classification accuracy was identified as the best model from each paper.

When available, the default rate for the lending institutions that had provided data to the researchers was reported.

Table 3: Summary of sample data collected by ComzAfrica

Summary Description	Value
Total loans	3,002,667
Total customers	41,391
Number of customers who repaid loans	21,608
Number of defaulters customers	19,783
Total months of data	16
Avg. loans per customer	72.5
Avg. amount borrowed per customer	35.05 USD
Avg.loans per month	187,666
Avg. loans per month per customer	4.5
Number of defaulted loans	30,809
Loan default rate	0.01%

Table 4: Summary of Feature Distribution

Variable	Status	Min	Max	Mean	Std Deviation
Average Loan duration (days)	Defaulters	0	290	9.3	14.14
	Non-Defaulters	0.27	505	9.58	16.11
Average Loan count	Defaulters	1	505	44.36	45.21
	Non-Defaulters	1	713	81.38	65.62
Average Usage amount (USD)	Defaulters	0	183.43	5.94	8.14
	Non-Defaulters	0	295.46	6.86	8.95

3.2 Data analysis

Building on this meta-analysis, the next step towards building a credit scoring model was to perform an exploratory analysis of the data and provide summary statistics about the variables. The dataset contains information collected from January 1st, 2016 to June 30th, 2017. Loans are considered from January 1st, 2016 to April 30th, 2017 in order to evaluate each individual customer's performance in the next three months (performance window) following the previous loan. Those who did not pay within the performance window are classified as defaulters. In the financial services sector, it is more important to predict those who will default than those who will repay. This is because the financial risk associated with defaulters is high. Table 7 describes this when calculating the specificity which measures the percentage of customers who are correctly identified as defaulting.

The table 3 shows the distributions of some of the main features; average loan duration, loan count and average usage amount for both non-defaulting and defaulting customers. The average is calculated because each customer could have accessed multiple loans in the past. All distributions are non-negative and right skewed with the majority of customers associated with smaller values. An inspection of non-defaulting and defaulting customers suggests remarkably similar behavior except for usage amount.

3.3 Feature engineering and selection

The Meta analysis suggests that features can be grouped into three categories: loan details, customer behavior and customer details (Age, Gender). The features that were available for this study were: loan amount, number of recharges for each month (how many times the customer recharged), usage amount (amount used the previous month), activation date (when the customer's account was activated), the date the loan was taken, the date of loan payment, and, total amount used every month. From the list of features above, this study is limited to the loan details and customer behavior. The customer details (Age, Gender) are available only to the MNO and not provided to ComzAfrica. Other features were also constructed based on the available variables and included: loan count (how many loans the customer has at any time), loan duration (how long the customer took to repay the loan), age on network (how long the customer has been with the MNO) and the loan month (the month that the loan was taken).

Table 5: Different cross validation scenarios and issues that they have

Issues	CV1	CV2	CV3
Randomness	Random loans	Random customer	Random customer and one loan
Evaluation	Evaluate loans	Evaluate loans	Evaluate customer
Time Issue	Y	Y	Y
Customer Issue	Y	N	N
Default Rate	<1%	<1%	5̃0%

Three different models structures were investigated. First, logistic regression (LR) provides binary classifications using linear relationships [18]. Second, a decision tree (DT) was constructed to assess the potential improvement using a nonlinear model [19]. Third, an ensemble approach known as Random Forest (RF) was deployed by averaging over a collection of decision trees [20].

3.4 Evaluation

To evaluate the model performance, it was necessary to create a distinct training and testing dataset in order to avoid over-fitting. Performance evaluation metrics can either be in-sample (data used for training is also used for testing) or out of sample (the data used to train the model is different from what is used for testing). An out-of-sample (OS) evaluation approach is required to ensure that the results are likely to generalize to new datasets. When dealing with data where the distribution of two prediction classes are highly imbalanced (low percentage of defaulters), a lot of care should be taken when creating the training and testing datasets. Three different cross-validation scenarios were investigated.

3.5 Cross-Validation Scenarios

The first scenario which we refer to as CV1 is where we split the loans in a ratio of 70:30 randomly without considering any variable. In this case neither time nor customer were considered. The repercussion is that a loan in the future can be used to predict a loan in the past. Furthermore this approach does not consider the customer either and this means that some of a customer's loans can be used for training and some for testing. To assess the problems associated with scenario CV1, it was necessary to consider a second scenario, referred to as CV2 where the loans are split in a ratio of 70:30 based on the customer. This means that a customer's loan can either be in training or testing but not both. This avoids situations where an individual customer's loans are being used for both training and testing. However CV2 did not address the time issue although it is not as flawed as the CV1 scenario.

In the two scenarios above, the default rate is less than 1%. This is a problem since if one guessed that the loan will be paid, they have a 99% chance of it being correct. This insight about the existence of a simple benchmark classifier motivated the third scenario, CV3. Each customers' loans details were first summarized and their last loan status was selected for entry. This reduced the size of the dataset to the number of customers available. The ratio of defaulting customers to non-defaulting customers was approximately 50:50 ensuring a balanced dataset with a default rate of 50% by design. The data was randomly split based on customers into 70:30 for training and testing. A customer can only be in one of the groups. This CV3 scenario therefore has no problem with repeat customers or time continuity. Table 6 summarizes the three scenarios and the characteristics of each one.

A confusion matrix was used to evaluate the classification models with positive (negative) outcomes denoting repayment (default) respectively. This 2x2 matrix measures the number of predicted/actual cases that are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). From this matrix it is possible to calculate the classification accuracy. The accuracy formula is given by:

$$ACC = (TP + TN)/(TP + TN + FN + FP)$$

Table 6: The distribution of customers in the test data in each scenario

Scenario	Defaulters	Non-defaulters
CV1	0.01%	99%
CV2	0.01%	99%
CV3	48%	52%

Table 7: Confusion matrix and associated impacts.

Actual Prediction	Predict Repaid	Predict Default
Actual Repaid	TP cost = +10%	FN cost=-100%
Actual Default	FP cost = -10%	TN cost = 0%

Table 7 shows the confusion matrix and the cost or benefit of each prediction. We are dealing with a cost-sensitive environment, where the class of interest is relatively rare, therefore accuracy is not the appropriate performance metrics. The greatest threat to financial sustainability is when the classifier predicts that a customer will repay the loan and they actually default (FN). Therefore it is more important to predict the customers who will not repay [21]. This can be assessed using the classification metric known as specificity. The formula is shown below:

$$Specificity = TN/(TN + FP)$$

Specificity measures the probability that a classifier produces a negative result for a non-defaulter, representing the percentage of non-defaulters that are correctly classified. We need to increase the true negatives and reduce the false positive.

4 Results

4.1 Model Evaluation

Table 8 shows the performance of all models for evaluations undertaken in-sample and using each of the three cross-validation scenarios. CV3 which had a balanced distribution of customers who repaid and defaulted, performed worse that the other two cross-validation scenarios. The reason is that the default rate of the two out-of-sample dataset is so high that the model will predict that loans will be good, which will be mostly correct. However when the default rate is close to 50%, it becomes more difficult for the model to generate accurate predictions although the specificity is high.

Table 9 shows the result of the confusion matrix of the random forest model.

5 Discussion

For the in-sample and first two cross-validation evaluations, CV1 and CV2, all models have high accuracy but struggled to achieve a reasonable specificity. Any simple benchmark classifier that predicts that all the loans will be repaid can easily achieve a high accuracy. However the low specificity reveals its inability to predict the customers who will default. In order to adequately

Table 8: Model evaluation results.

Model	Evaluation Metric	In-sample	CV1	CV2	CV3
LR	ClassAcc	99.1%	99.1%	99.1%	80.0%
	Specificity	0.2%	0.2%	0.2%	78.8%
DT	ClassAcc	99.1%	99.1%	99.0%	79.7%
	Specificity	0.0%	0.0%	0.0%	79.8%
RF	ClassAcc	99.1%	99.1%	99.9%	82.3%
	Specificity	0.8%	0.0%	0.0%	84.7%

Table 9: Confusion matrix of random forest model for CV3

Actual Prediction	Predict Repaid	Predict Default
Actual Repaid	85%	15%
Actual Default	20%	80%

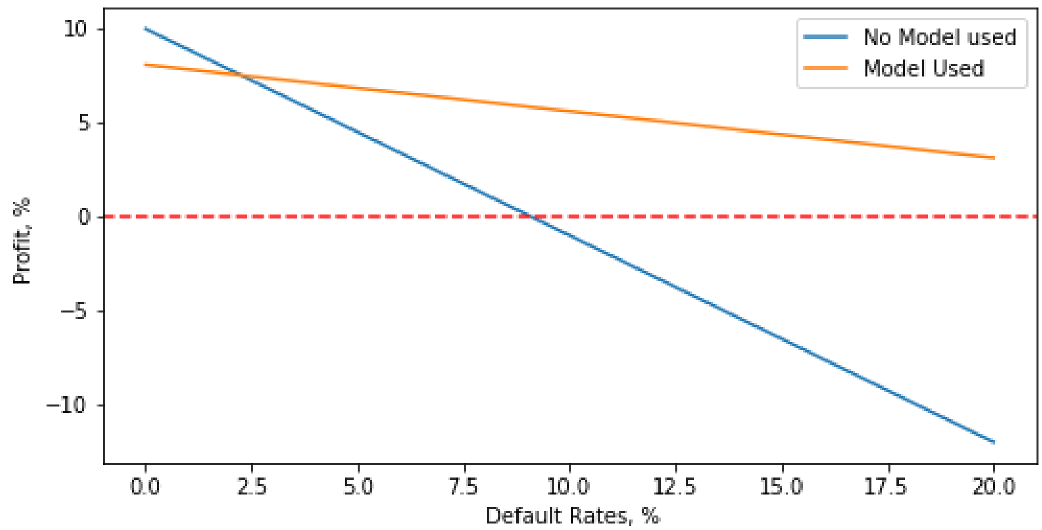

Figure 1: Profit generated by a company charging 10% interest on each loan for a range of default rates

evaluate the potential of predicting the customers who will default, more data about loans and customers who defaulted is required. That is why evaluation scenario CV3 specifically operates on a dataset with one loan per customer and approximately half of these resulted in default by design to obtain a balanced set of categories. The variables collected provided information about previous loans. Adding the month that the loan was borrowed as dummy variables increased the accuracy of the model. This is likely due to annual seasonality in customer's incomes. The number of recharges was not selected as a relevant variable.

Nonlinearity was relevant with both the decision tree and random forest beating logistic regression in terms of specificity. Random forest was superior with an accuracy of 82.3% and specificity of 84.7% for CV3, confirming the advantages of the ensemble approach.

When the default rate is as low as 0.01%, it is better to accept all the loan request. The model cannot beat this approach. However as the default rate increases to > 2%, the company will make more profit if they use the model compared to awarding everyone with a loan. Figure 1 shows the profit as the default rate increases. This is calculated by adding the total value of the loan to the interest that will incurred then subtracting the loans that were defaulted. When there is no default, the company will make a profit equal to the interest rate. The company breaks even with zero profits at a default rate of 8%. In contrast, when one uses the model, the maximum default rate that the company can tolerate before making losses is 32%. This means that the model effectively quadruples the level of default risk that can be tolerated.

6 Conclusion

We can conclude the following from our research:

- For a classification problem with an imbalanced number of categories, classification accuracy is not an appropriate performance metric. One solution is to use specificity instead in order to focus on the classifier's ability to predict the occurrence of a particular category. In the case of credit scoring, predicting defaulters is of utmost importance.

- Great care is required when selecting the appropriate cross-validation technique. There are many factors that affect the data structure and specific application that should be taken into consideration. For credit scoring, handling of time of loan and customer identity are crucial.
- It would be beneficial to have access to more variables. The literature review suggests that obtaining customer details from the MNOs would improve performance.
- Both nonlinear classification models outperformed logistic regression.
- Random forest was the best classifier with an accuracy of 82.3%.
- When the default rate is low, it is better to offer the loans to every customer however after a certain point, the model will outperform offering loans to everyone.
- The maximum tolerable default rate is increased by the model to 32% compared to 8% when the company does not use a model.
- The above methodology can be used in other industries where credit is given to basic services such as electricity token, smart water meters, smart cooking gas and solar energy.

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